Incorporating Probabilistic Optimizations for Resource Provisioning of Data Processing Workflows

Amelie Chi Zhou, Yao Xiao, Bingsheng He, Shadi Ibrahim, Reynold Cheng

Incorporating Probabilistic Optimizations for Resource Provisioning of Data Processing Workflows

Amelie Chi Zhou[1] Yao Xiao [1] Bingsheng He[2] Shadi Ibrahim[3] Reynold Cheng[4]

[1] *Shenzhen University* [2] *National University of Singapore* [3] *Inria, IMT Atlantique, LS2N* [4] *The University of Hong Kong*

ABSTRACT

Workflow is an important model for big data processing and resource provisioning is crucial to the performance of workflows. Recently, system variations in the cloud and large-scale clusters, such as those in I/O and network performances, have been observed to greatly affect the performance of workflows. Traditional resource provisioning methods, which overlook these variations, can lead to suboptimal resource provisioning results. In this paper, we provide a general solution for workflow performance optimizations considering system variations. Specifically, we model system variations as time-dependent random variables and take their probability distributions as optimization input. Despite its effectiveness, this solution involves heavy computation overhead. Thus, we propose three pruning techniques to simplify workflow structure and reduce the probability evaluation overhead. We implement our techniques in a runtime library, which allows users to incorporate efficient probabilistic optimization into existing resource provisioning methods. Experiments show that probabilistic solutions can improve the performance by 51% compared to state-of-the-art static solutions while guaranteeing budget constraint, and our pruning techniques can greatly reduce the overhead of probabilistic optimization.

KEYWORDS

Resource provisioning, Cloud dynamics, Workflows

1 INTRODUCTION

In many data-intensive applications, data processing jobs are often modeled as workflows, which are sets of tasks connected according to their data and computation dependencies. For example, Montage workflow [20] is an astronomy-related big data application, which processes sky mosaics data in the scale of hundreds of GBs. Large companies such as Facebook, Yahoo, and Google frequently execute ad-hoc queries and periodic batch jobs over petabyte-scale data based on MapReduce (MR) workflows [30]. Those data-intensive workflows are usually executed in large scale systems and *resource provisioning*, which determines the size and type of resources to execute workflow tasks, is important to the performance of workflows and has been widely studied by existing work [14, 15, 18].

In many large-scale systems, variations have become the norm rather than the exception [8, 27]. Variations can be caused by both hardware and software reasons. For example, in supercomputer architectures, the variation in power and temperature of the chips can cause up to 16% performance variation between processors [1]. In cloud environments, network and I/O performances also show significant variations due to user interferences [27]. Job failures have been demonstrated to be variant and follow different kinds of probability distributions for different systems [8]. These variations, which have been ignored by most existing optimization methods, raise new challenges to the resource provisioning problem of workflows. In this paper, we focus on the cloud system, aiming at proposing a general solution to incorporating system variations for resource provisioning problems of workflows.

Why consider variations? Cloud providers offer various types of instances (i.e., VMs) for users to select the most appropriate resources to execute workflow tasks. Most existing resource provisioning methods assume that the execution time of each task is static on a given type of VMs. However, this assumption does not hold in the cloud, where *cloud dynamics*, such as the variations of I/O and network performances, can result in major performance variation [22, 27] to large-scale data processing workflows. We analyzed several common resource provisioning problems for workflows, and observed that the performance optimization goal is usually *nonlinearly* related to the cloud dynamics in I/O and network performance. Thus, traditional *static* optimizations (e.g., taking the *average* or *expected* I/O and network performance as optimization input) can lead to suboptimal or even infeasible solutions (theoretically explained in Section 3).

Why probabilistic method? Existing studies propose various methods such as dynamic scheduling [10, 15] and stochastic modeling [2, 11] to address resource provisioning problems considering cloud dynamics. However, these methods either rely on accurate cloud performance estimation at runtime or involve complicated modeling and analysis and thus hard to generalize. For example, Adam et al. [2] employ the G/G/m queuing model for resource provisioning of containerized web services in clouds, and Huang et al. [11] address spot price dynamics based on Markov decision processes. In this paper, we study a systematic and effective way of incorporating cloud dynamics into resource provisioning of workflows. We model cloud dynamics as random variables and take their *probability distributions* as optimization input to formulate resource provisioning problems. This design has two main advantages. First, it enables probabilistic analysis required by many problems with system randomness, such as designing fault-tolerant scheduling techniques for workflows in case of random system failures [25]. Second, it enables the derivation of probabilistic bounds [26] to guarantee the worst-case performance of applications, while the existing static methods only guarantee the average performance.

Why this paper? With the probabilistic representation of cloud dynamics, traditional static resource provisioning methods cannot be used directly. The main challenge is that using probability distributions as optimization input leads to a significantly high computation overhead due to the costly distribution calculations and complex structures of data processing workflows. There exist some techniques to improve the efficiency of probabilistic optimization in various fields, such as efficient query evaluations in probabilistic databases [5], accurate data processing with uncertain data [16] and efficient probabilistic cluster scheduling with runtime uncertainty [23]. However, these techniques either rely on given probability distributions [16] or do not consider the special features of workflow structure and resource provisioning problems [23], which can help to more efficiently reduce the overhead of probabilistic resource provisioning of workflows.

Contributions: We propose *Prob* to efficiently incorporate cloud dynamics into resource provisioning for workflows, without any assumption on the distribution of cloud dynamics. *Prob* has three simple yet effective pruning techniques to reduce the overhead of probabilistic optimizations. These techniques are designed based on features of workflow structures and resource provisioning problems. First, we identify that calculating the makespan of a workflow is a common operation in many resource provisioning problems. We propose pre-processing pruning to reduce the overhead of this important calculation and hence reduce the overhead of probabilistic optimizations. Second, we propose workflow-specific optimizations using existing workflow transformations to reduce the overhead of evaluating one resource provisioning solution. Third, we propose a partial solution evaluation method and adopt an existing pruning technique to reduce the overhead of comparing multiple solutions.

We develop a runtime library that includes all the pruning techniques of *Prob*. Users can implement their *existing* resource provisioning methods using *Prob* APIs to incorporate probabilistic optimizations, in order to improve both the effectiveness and efficiency of existing methods. We experimented with real-world workflows on Amazon EC2 and with simulations to show the effectiveness of probabilistic optimizations and our pruning techniques. Our experiments demonstrate up to 51% performance improvement of probabilistic solutions compared to state-of-the-art static solutions. The pruning techniques of *Prob* bring significant reduction to the overhead of probabilistic solutions (e.g., 450x speedup compared to the Monte Carlo (MC) method).

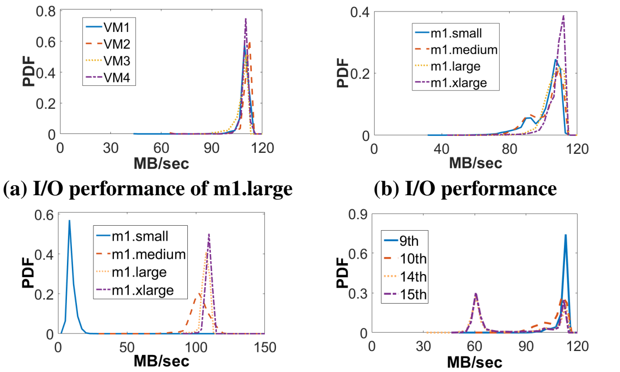
Goals and non-goals: Our goal is to propose an efficient interface for existing resource provisioning methods to easily incorporate probabilistic optimizations, rather than proposing a new resource provisioning method. To show the generality of *Prob*, we use a common workflow resource provisioning problem as use case and discuss how *Prob* can improve the effectiveness of existing solutions.

2 PRELIMINARIES

2.1 Data Processing Workflows

A data processing workflow (a job) can be described as a directed acyclic graph (DAG) [7]. A vertex in the DAG represents a task in the workflow while an edge represents the data dependency between two tasks. A task in a workflow performs certain data transformation to its input data. We adopt an existing approach [31] widely used for data-intensive task execution time estimation, which calculates the task execution time as the sum of the CPU, I/O and network time. We define a virtual entry vertex and a virtual exit vertex in a workflow. The entry vertex does nothing but staging input data of the workflow while the exit vertex saves output results.

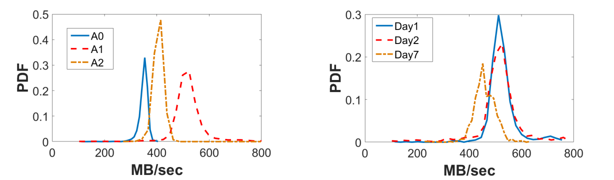
Resource provisioning for a workflow in the cloud decides the number and types of cloud instances required for executing the workflow. Performance is an important optimization metric for resource provisioning of data-intensive workflows and can be highly affected by resource provisioning decisions. Various methods have been proposed to optimize either the performance of workflows in the cloud [8, 18] or the monetary cost/energy efficiency of workflows with performance constraints [12, 14, 15].



(a) I/O performance of m1.large (b) I/O performance

(c) Network performance (d) I/O perf. of m1.large in Sep.

Figure 1: Cloud dynamics features observed on Amazon EC2.



(a) I/O performance (b) I/O performance of A1

Figure 2: Cloud dynamics features on Windows Azure.

2.2 Cloud Dynamics Terminology

In this paper, we study two kinds of variations, namely the I/O and network performance variations, which are common in the cloud and decisive to the performance of workflows (the CPU performance is rather stable in the cloud [27]). We extend the analysis to other system variation factors in our technical report [33]. Formally, we define the I/O (network) performance dynamics as below.

DEFINITION 1. *We view the I/O (network) bandwidth assigned to a running task as a random variable (r.v.) X. The I/O (network) bandwidth dynamics can be described with a probability distribution (PDF) $f_X(x)$, which represents $P(X = x)$.*

The above definition greatly changes the formulation and solving of resource provisioning problems for workflows in the cloud. Consider a simple example of calculating the *expected* I/O time of a task. With the static definition of I/O bandwidth as a scalar value b_{io} ($b_{io} = \sum_x x \cdot f_X(x)$), we have $t_{io} = \frac{d_{io}}{b_{io}}$, where d_{io} is the I/O data volume of a task and t_{io} is the I/O time. With our definition of I/O bandwidth dynamics, the value of t_{io} is also dynamic. Defining the I/O time of the task with r.v. T, we can use the PDF of I/O bandwidth to calculate the distribution of T as $f_T(t) = f_X(\frac{d_{io}}{t})$. The expected value of T is $\sum_x \frac{d_{io}}{x} \cdot f_X(x)$ and can be different from the result of the static method (i.e., $\frac{d_{io}}{\sum_x x \cdot f_X(x)}$).

2.3 Features of Cloud Performance Dynamics

We study the spatial and temporal features of cloud performance dynamics in I/O and network. We demonstrate that the probability distributions of performance dynamics are predictable in a short period of time. We conduct the experiments on Amazon EC2 cloud. More details about the measurements can be found in Section 5.

Spatial features. The performance of instances of the same type can be modeled with similar/the same probability distributions. Figure 1a shows the distributions of the sequential I/O performances of four m1.large instances running on the same day, which follow very similar distributions. We performed the measurements on over 100 instances and found consistent results.

Another observation is that, the probability distributions of performances of different types of instances usually have similar patterns with different parameters. Figure 1b and 1c show the sequential I/O and network performance distributions of four instance types, respectively. For each type, data are collected from multiple instances over 1 day. The distributions have similar patterns with different mean and variances. For example, the mean network bandwidth is higher on more expensive instance types such as m1.large and m1.xlarge and the performance variance is more severe on cheap instance types such as m1.small and m1.medium.

Temporal features. The probability distributions of the cloud performance are stable within a short time period. Figure 1d shows the sequential I/O performance distributions of m1.large instances measured on the 9th, 10th, 14th and 15th September, 2015, where distributions in a short period of time are closer to each other in terms of mean and variance. Quantitatively, we adopt the *Bhattacharyya distance* [3], a commonly used statistical metric, to measure the similarity of two distributions (smaller distance indicates higher similarity). The distance between the I/O performance distribution of the 9th and that of the 10th is only 0.03, while the distance between the distributions of the 9th and the 14th is 0.1. This means that the I/O performance distribution in a short period of time (e.g., one day) is more stable than that in a longer period (e.g., five days). The same observation has also been found on the network performances.

To demonstrate the generality of our observations, we perform similar experiments on Windows Azure using three general purpose instance types, namely A0, A1 and A2. Figure 2a demonstrates that the spatial feature can also be observed on Azure, where distributions of the sequential I/O performance of different instance types follow similar patterns with different parameters. A1 has higher performance variation than the other two types. We suspect it is because A1 is the recommended type of Azure and thus has more users. Figure 2b shows that the temporal feature also holds on Azure, where the I/O performance distribution of A1 measured in Day 1 is more similar to that of Day 2 than that of a longer period in Day 7.

Summary: The spatial and temporal predictability of cloud dynamics verifies that it is feasible to represent cloud dynamics using their distributions and adopt probabilistic methods to optimize the resource provisioning problems.

3 PROBABILISTIC APPROACH IS NEEDED

As a motivating example, we present a common resource provisioning problem for workflows in the cloud. We first present an *existing* solution [32] to this problem under static performance notions and then discuss our solution considering cloud dynamics. We show that cloud dynamics can greatly affect the optimization effectivenesses. All the mathematical proofs can be found in our technical report [33].

3.1 Budget-Constrained Scheduling Problem

Cloud providers offer multiple instance types with different capabilities and prices. In this problem, we aim to select a suitable instance type for each task in a workflow to minimize workflow execution time while satisfying budget constraint.

Consider a workflow with N tasks running in a cloud with K types of instances. The optimization variable of this problem is vm_{ij}, meaning assigning instance type j ($j = 0, 1, \ldots, K-1$) to task i ($i = 0, 1, \ldots, N-1$). The value of vm_{ij} is 1 (i.e., task i is assigned to instance type j) or 0 (otherwise). We denote the execution time of task i on instance type j using r.v. T_{ij} with a probability distribution $f_{T_{ij}}(t)$. We denote the workflow execution time (i.e., makespan) with r.v. T_w and calculate its distribution $f_{T_w}(t)$ using the execution time distributions of tasks on the critical path (denoted as CP). The user-defined budget constraint is denoted as B, which includes the instance rental cost and networking cost. The unit time rental price of instance type j is denoted as U_j. The networking cost of task i transferring data to its child tasks is denoted as C^i_{net}. $E[X]$ denotes the expected value of a r.v. X. We formulate the problem as below.

$$\min E[T_w] = \min E[\sum_j \sum_{i \in CP} T_{ij} \times vm_{ij}] \quad (1)$$

s.t.

$$\sum_i \{\sum_j E[T_{ij}] \times vm_{ij} \times U_j + C^i_{net}\} \le B \quad (2)$$

$$\sum_j vm_{ij} = 1, \forall i \in 0, \ldots, N-1 \quad (3)$$

3.2 A Static Solution

The budget-constrained scheduling problem has been widely studied [14, 18] using either heuristics or model-based methods. However, most of them assume static task execution time during the optimization. We first introduce a traditional static approach for the budget-constrained scheduling problem, and discuss how to incorporate cloud dynamics next.

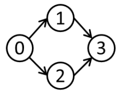
We adopt an existing method [32] which formulates resource provisioning problems as search problems, and adopt generic search or more efficient $A^\star$ search to find a good solution. We choose this algorithm for its generality. We briefly present the behavior of the search algorithm as below (see also Algorithm 1).

A state s in the solution space is modeled as a N-dimensional vector, where s_i stands for the instance type assigned to task i. Correspondingly, vm_{ij} equals to 1 if $j = s_i$ and 0 if otherwise. It searches the solution space in a BFS-like manner. Each found solution is evaluated using Equation 1 for the optimization goal and Equation 2 for the budget constraint. The static optimizations take the expected I/O and network performance as input to estimate the task execution time. That means, T_{ij} is only a scalar value and computing Equation 1 and 2 is light-weight. After evaluating a solution, we compare it with the best found solution and keep the one with better evaluation result while meeting the constraint. The search process terminates if the entire solution space has been traversed or a predefined number of iterations has been reached.

3.3 A Probabilistic Method

To incorporate cloud dynamics into the static method, we have made two efforts. First, we take the I/O and network performance dynamics of instance type j to estimate the probability distribution of T_{ij}. Second, whenever T_{ij} is used in the search process, we perform probabilistic calculations on distributions, e.g., adding task execution time distributions to obtain path execution time distribution, finding the maximum execution time distribution of multiple paths (i.e., finding the critical path) to evaluate the optimization goal in

Tid1	Tid2	Time	p
0	1	100	0.6
0	1	130	0.3
0	1	170	0.1
0	2	100	0.6
0	2	130	0.3
0	2	170	0.1
1	3	130	0.7
1	3	140	0.2
1	3	150	0.1
2	3	120	0.5
2	3	145	0.3
2	3	160	0.2



Path 1: 0 → 1 → 3
Path 2: 0 → 2 → 3

- Static method: $T_{path} = \sum_{i \in path} E(T_i)$
  $E[MAX(T_1, T_2)] = 251.5$
- Probabilistic method: $\overrightarrow{T_{Path}} = \sum_{i \in path} \overrightarrow{T_i}$
  $E[MAX(\overrightarrow{T_1}, \overrightarrow{T_2})] = 257.4$

Figure 3: An example of probabilistic optimizations.

Equation 1, and comparing evaluation metric distributions of two found solutions to find a good solution.

The distribution addition with two independent r.v., e.g., $Z = X + Y$, can be calculated as below.

$$f_Z(z) = \int_{-\infty}^{\infty} f_Y(z - x) f_X(x)\, dx \tag{4}$$

Finding the maximum distribution of two independent r.v., e.g., $Z = max\{X, Y\}$, can be calculated as below. $F_X(x)$ and $F_Y(y)$ are the cumulative distribution functions (CDFs) of X and Y, respectively.

$$f_Z(z) = \frac{d}{dz} F_Y(z) F_X(z) = F_Y(z) f_X(z) + F_X(z) f_Y(z) \tag{5}$$

We adopt the following definition to compare two evaluation metric distributions. Given two independent r.v. X and Y, we have $X > Y$ if $P(X > Y) > 0.5$, where

$$P(X > Y) = \int_{-\infty}^{\infty} \int_{y}^{\infty} f_X(x) f_Y(y)\, \mathrm{d}x\, \mathrm{d}y \tag{6}$$

Figure 3 gives a concrete example to show the difference between static and probabilistic optimizations. Consider the budget-constrained scheduling for a workflow with four tasks. The execution time distributions of tasks have been calculated using I/O and network performance distributions, as shown in the table. There are 2 paths in the workflow. To optimize workflow performance, we need to identify the critical path and schedule tasks on the critical path to more powerful VMs. We make the following observations.

Probabilistic optimization is more effective. With the traditional static method, the expected lengths of edges are used for evaluations and path 2 is returned as the critical path with a length of 251.5. With our probabilistic method (introduced in details in Section 4), we first calculate the length distributions of the two paths and then calculate the maximum of the two distributions. Given the length distributions of path 1 and 2 (denoted as $\vec{T_1}$ and $\vec{T_2}$, respectively), the expected length of the critical path is 257.4. The probability of path 2 being the critical path is only 0.48. Theoretically, this observation is supported by the following lemma, which shows that for parallel structured workflows, static methods using average task execution time as input always *under-estimate* the expected workflow execution time.

LEMMA 1. *Given two independent r.v. X and Y, for the r.v.* $Z = max\{X, Y\}$*, we have* $E[Z] \geq max\{E[X], E[Y]\}$.

For workflows with complex structures, the estimation errors of static methods can accumulate and lead to more inaccurate or even incorrect optimization results. Consider the above example with a workflow structured as two of the same workflow in Figure 3 standing in parallel. The expected workflow execution time calculated using the static and probabilistic methods are 251.5 and 271.6, respectively. Thus, the under-estimation problem is more severe for workflows with complex structures and it is important to consider cloud dynamics for resource provisioning of workflows.

Probabilistic optimization is costly. A straight-forward way to implement probabilistic optimization is to use the sampling-based Monte Carlo (MC) approach, which calculates all possible results using input probability distributions. For example, to obtain the sum distribution of Equation 4, we perform M times of MC calculations. In each calculation, we randomly sample values from the discretized distributions $f_X(x)$ and $f_Y(y)$ to get a possible result of the sum. After the M times calculations, we can create the sum distribution using the M calculated sum results. Thus, the time complexity of adding two task execution time distributions is $O(M)$ and for adding n tasks is $O((n-1)M)$. Note that M is usually very large to achieve good accuracy. For a workflow with complex structure and a large number of tasks, the time complexity for calculating the workflow execution time distribution is high. Similarly, with the MC approach, the time complexity of calculating the maximum distribution is $O(M)$ and of comparing two evaluation metric distributions is $O(M^2)$. Thus, the computation overhead of probabilistic optimization is prohibitively high due to the large M, complex workflow structures and costly distribution comparisons.

In summary, probabilistic distributions improve the effectiveness of workflow optimizations in dynamic clouds while causing a large overhead. This motivates us to develop an effective and efficient approach for resource provisioning of workflows in the cloud.

4 DESIGN OF PROB

We propose a probabilistic optimization approach named *Prob* for incorporating cloud dynamics into workflow optimizations. We introduce three simple yet effective pruning stages in *Prob* to address the large overhead of probabilistic optimizations caused by complex workflow structures and costly calculations and comparisons of distributions. First, calculating the makespan of a workflow is a common operation in many resource provisioning problems of workflows. Thus, we propose pre-processing pruning to reduce the overhead of this important calculation and hence reduce the overhead of probabilistic optimizations. This stage is an offline optimization stage, as a workflow only needs to be optimized once and for all. Second, we propose workflow-specific optimizations using existing workflow transformation techniques to reduce the overhead of evaluating one resource provisioning solution. Third, we propose two pruning techniques to reduce the overhead of comparing multiple solutions. The latter two stages are called at the runtime of solution search process.

4.1 Pre-Processing

Calculating the execution time of a workflow is a common operation in many resource provisioning problems of workflows. Due to cloud dynamics, the execution time of a workflow is represented as a random variable. To obtain its probability distribution, we first decompose a workflow into a set of paths starting from the entry to the exit task of the workflow. The execution time distribution of the workflow is the maximum of execution time distributions of all paths in the set. We further propose a *critical path pruning* and a *path binding* technique to reduce the number of paths in the set and hence reduce the overhead of calculating workflow

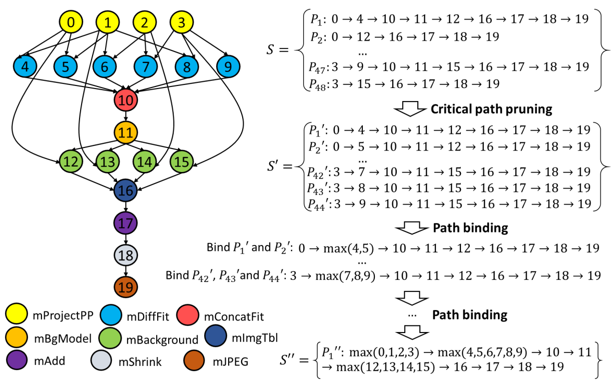


Figure 4: Example of pre-processing using Montage workflow.

execution time distribution. In Figure 4, we use the structure of a real-world scientific workflow named Montage [24] to demonstrate the effectiveness of the two pruning techniques.

Given a workflow, we can easily enumerate all paths in the workflow using depth-first search in $O(2^V)$ time, where V is the number of vertices in the workflow. Although the exponential time complexity is not ideal, the pre-processing optimization is at offline time and only has to be performed once for a given workflow structure. The pre-processing results can be used for all further optimization problems of the same workflow structure. Assume all paths from the entry task to the exit task are stored in a set S. We introduce the following two techniques to reduce the size of S.

Critical Path Pruning. This technique eliminates the paths that are impossible to be the critical path from S. For example, in Figure 4, as the execution time of path P_2 must be shorter than that of P_1, clearly P_2 is not the critical path. Similarly, path P_{48} is impossible to be the critical path due to P_{47}. We can eliminate such paths from S and reduce the size of S from 48 to 44. We denote the set of paths after pruning as S'.

The critical path pruning follows the following rule: given any two paths P_1 and P_2 between the entry and exit tasks of a DAG, if the set of nodes in P_1 is a subset of that in P_2, P_1 is not the critical path. We order all paths in S according to their lengths, and iteratively compare the longest path with the ones shorter than it using the above rule. The expected time complexity of this technique is $O(|S| ln|S| \times L)$, where L is the average length of paths in S.

Path Binding. Given S' in Figure 4, we need in total 352 distribution additions to evaluate path distributions and 43 distribution maximum operations to obtain workflow execution time distribution. However, we find that when evaluating P'_1 and P'_2 separately, many of the distribution additions are repetitive. By binding P'_1 with P'_2, we can reduce the overhead from 16 distribution additions to 8 distribution additions and one operation on calculating the maximum distribution of task 4 and 5. We can apply the binding to all paths in S' and reconstruct them to a single path as shown in S''. With S'', the overhead of calculating the workflow execution time distribution is reduced to 8 distribution additions and 11 distribution maximum operations. As the distribution addition and maximum operations have the same time complexity with the MC method, path binding reduces the overhead of calculating workflow execution time distribution by 95%.

Formally, the path binding technique binds two paths with the same length L in the following way. We compare each node of one path with the node in the same position of the other path in order. If the i-th nodes ($i = 0, \ldots, L-1$) are the same, they are adopted as the i-th node of the binded path. Otherwise, we bind the i-th nodes of the paths as one node, the execution time of which is the maximum of the i-th nodes of the two paths. Assume there are k binded nodes in the binded path, the calculations saved by binding the two paths is $L - k - 1$. We iteratively select two paths in S' with the best gain to bind until no gain can be further obtained or the largest number of iterations have been reached. This technique is especially useful for data processing workflows such as MR jobs, where the input data partitions go through the same levels of processing (i.e., all paths have the same length). The expected time complexity of this pruning is $O(|S'| ln|S'| \times L)$, where L is the average length of paths in S'.

Note that the pre-processing only needs to be applied once at offline time and the results can be reused for different resource provisioning problems of the same workflow structure.

4.2 Workflow-Specific Optimizations

After the pre-processing stage, evaluating a found solution, namely calculating the execution time distribution of a workflow according to the instance configurations indicated by the solution, is simplified to calculating the distributions of several paths. The workflow execution time distribution is calculated as the maximum distribution of all path distributions.

We decompose the calculation of workflow execution time distribution to two constructive operations, namely *ADD* and *MAX*. The *ADD* operation can be applied to the distributions of two dependent tasks while the *MAX* operation can be applied to the distributions of two parallel tasks or two paths from the pre-processing result. We define *ADD* and *MAX* as binary operators, which operate on two probability distributions at a time. To apply *ADD* and *MAX* on n ($n > 2$) distributions, we perform the operators $n-1$ times. For example, the execution time distribution of path P_2 in Figure 4 can be calculated as

$$\begin{aligned} PDF_{P_2} = & ADD(ADD(ADD(ADD(ADD(PDF_0, PDF_{12}), \\ & PDF_{16}), PDF_{17}), PDF_{18}), PDF_{19}) \end{aligned} \tag{7}$$

where PDF_i denotes the execution time distribution of task i on the instance type assigned by the current evaluated solution.

The calculation of *ADD* and *MAX* operations are introduced in Equations 4 and 5, respectively. As discussed in Section 3, a straightforward implementation for *ADD* and *MAX* is to use the sampling-based MC method. However, this implementation can lead to a large overhead due to complex workflow structures and the large sampling size. Thus, we adopt two existing workflow transformation optimizations to reduce the overhead while preserving the correctness of *ADD* and *MAX* operations.

For many resource provisioning problems of workflows, existing studies have proposed various workflow transformations to simplify workflow structures, such as *task bundling* [17] and *task clustering* [28]. Both operations attempt to increase the computational granularity of workflows and reduce the resource provisioning overhead. In this paper, we discuss the two operations from the perspective of probabilistic optimizations.

Optimizing *ADD* with task bundling. Task bundling treats two pipelined tasks with the same assigned instance type as one task, and schedules them onto the same instance sequentially. For example, in Figure 4, we can bundle tasks 10 and 11 in P_1'' as one task when they have the same assigned instance type. Task bundling can increase instance utilization and reduce the amount of data transfer between dependent tasks. This technique gives us the opportunity to reduce the overhead of *ADD* operation.

When applying the *ADD* operation on two tasks, if the tasks satisfy the requirement of task bundling, we can directly generate the resulted distribution using the I/O and network profiles of the two tasks without calculating their distributions separately. With the naive MC implementation, the number of computations of the *ADD* operation is $3M$, which includes the computations for generating execution time distributions of two tasks and the computations for calculating the sum distribution. M is the number of MC calculations as mentioned in section 3.3. After applying task bundling, the number of computations of *ADD* is reduced to M.

Optimizing *MAX* with task clustering. In many data processing workflows, the data volume to be processed is huge. The execution is usually in a data parallel manner. Data are divided into a large number of partitions with equal sizes and are processed in parallel with many tasks. We denote those parallel tasks as *equivalent tasks*. In scientific workflows, tasks on the same level, using the same executable for execution and having the same predecessors are identified as equivalent tasks. In MR workflows, we can easily identify the map/reduce tasks on the same level as equivalent tasks.

Task clustering groups two equivalent tasks assigned to the same instance type as one task and schedules them onto the same instance for parallel execution. For example, in Figure 4, tasks 12 to 15 in P_1'' can be identified as equivalent tasks and grouped as one task with three times of clustering. Note that, the four tasks cannot be viewed as equivalent tasks before the pre-processing (e.g., in S and S'), since they have different predecessors. The task clustering technique offers opportunity to reduce the overhead of *MAX* operation.

As equivalent tasks have the same (or similar) resource requirements and are executed on the same instance in parallel, we can use the execution time distribution of one of the equivalent tasks to represent the distribution of the clustered task. This can be verified with Lemma 1, where $E[max\{X, Y\}] = E[X] = E[Y]$ when X and Y are the same random variable. However, we must consider the performance degradation of the clustered tasks due to resource contention. Thus, when applying the *MAX* operation on two tasks, if they satisfy the requirement of task clustering, we use $f_X(\frac{x}{2})$ to represent the resulted distribution assuming $f_X(x)$ is the execution time distribution of one of the two tasks. With this optimization, we reduce the overhead of *MAX* from $O(M)$ to $O(1)$. The number of equivalent tasks to be clustered is determined by the resource capacity of the instance and the resource requirement of tasks.

4.3 Distribution-Specific Optimizations

Given two resource provisioning solutions (i.e., two vectors of instance configurations for each task in the workflow), we evaluate each solution and compare their evaluation metric distributions to find a good solution. In the above, we have proposed to reduce the overhead of evaluating one solution. In this subsection, we mainly focus on reducing the overhead of solution comparisons to reduce the overhead of probabilistic optimizations. Specifically, we propose a partial solution evaluation technique and adopt an existing pruning in probabilistic database to reduce the overhead of solution comparisons.

Partial solution evaluation. As the purpose of solution evaluations is to compare their quality and find a good one, we propose a partial solution evaluation technique to avoid fully evaluating two solutions while guaranteeing the same solution comparison result. When evaluating two solutions s and s', we only calculate the distributions of tasks with different configurations in s and s' (i.e., $\forall i$ where $s_i \neq s_i'$). Comparing the partially evaluated distribution of s with that of s' gives the same result as comparing the fully evaluated distributions. This property is guaranteed by Lemma 2.

LEMMA 2. *Given two r.v. X and Y, assume $X > Y$. Then we have $g(X, Z) > g(Y, Z)$ for any r.v. Z independent from X and Y, where $g(\cdot)$ is either ADD or MAX.*

Consider two solutions s and s' for the workflow in Figure 4. Assume s differs from s' on the configurations of task 10 and 11. With the partial evaluation, s' results in shorter workflow execution time than s if

$$P(ADD(PDF_{10}^{s}, PDF_{11}^{s}) > ADD(PDF_{10}^{s'}, PDF_{11}^{s'})) > 0.5 \tag{8}$$

where PDF_i^s and $PDF_i^{s'}$ are the execution time distributions of task i on the instance type assigned by s and s', respectively. In this way, we reduce the overhead of comparing the two solutions from 38 probabilistic operations (either *ADD* or *MAX*) and one distribution comparison to two *ADD* and one distribution comparison.

Assume we visit in total n solutions during the solution search process, the overhead of full solution evaluations would be $O(n \times (N-1) \times M)$, where N is the number of tasks in a workflow. With our partial evaluation technique, assume the average number of different configurations in a pair of solutions is N', the overhead of solution evaluations is reduced to $O(2n \times (N' - 1) \times M)$. For many resource provisioning algorithms, such as the search algorithm introduced in Section 3.2, adjacent solutions on the search tree only differ by a few configurations (i.e., $N' \ll \frac{N}{2}$). Thus, partial solution evaluation can greatly reduce solution search overhead. This pruning can be disabled when comparing two solutions where half of the tasks are assigned with different configurations.

Distribution comparison pruning. After solution evaluations (either partial or full), we repeatedly use Equation 6 for distribution comparisons during solution search process. The complexity of one distribution comparison is $O(M^2)$, which is extremely high due to the large sampling size M. Thus, we adopt an existing pruning technique [5] in probabilistic database to prune the unnecessary calculations of Equation 6. The basic idea is described as below.

Assume random variable X (resp. Y) has the lower and upper bound of $X.l$ (resp. $Y.l$) and $X.r$ (resp. $Y.r$), respectively. With Equations 9 and 10, we can estimate the lower bound or upper bound of $P(X > Y)$. If the lower bound is greater than 0.5 or the upper bound is less than 0.5, we can prune the calculation of Equation 6.

$$\text{If } X.l \leq Y.r \leq X.r,\ P(X > Y) \geq 1 - F_X(Y.r) \tag{9}$$

$$\text{If } X.l \leq Y.l \leq X.r,\ P(X > Y) \leq 1 - F_X(Y.l) \tag{10}$$

5 SYSTEM IMPLEMENTATION

Figure 5 shows the integration of *Prob* in existing data processing systems (e.g., Hadoop). We introduce two main design details of *Prob*. First, *Prob* stores system states (e.g., cloud performance

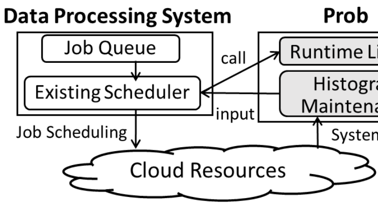


Figure 5: System overview

calibrations) and maintains the histograms (i.e., discrete distributions) of cloud dynamics. Those distributions are taken as input by *Prob*-enabled system schedulers to find the optimal resource provisioning solution. Second, *Prob* offers a runtime library which exposes the probabilistic operations (e.g., *ADD* and *MAX*) and pruning techniques designed for resource provisioning problems of workflows. Existing schedulers of data processing systems can call the APIs in the library when implementing their resource provisioning methods to incorporate probabilistic optimizations. The data processing system schedules jobs to the cloud resources according to the optimized resource provisioning solutions.

5.1 Maintenance of Probability Distributions

As optimization inputs, we consider two types of system states, including 1) instance-related states such as price, CPU, I/O and network performances and 2) job-related states such as job start time and finish time. *Prob* collects those states from the cloud and maintains the data in an online and lightweight manner.

Data collection. System states are calibrated and updated periodically. Instance-related states are measured from the cloud platform by opportunistically taking the idle time of running instances. As the CPU performance is rather stable in the cloud, we mainly focus on calibrating I/O and network performances. We measure the sequential I/O reads performance (reads and writes have similar performances) of local disks with hdparm and the network bandwidth between two instances with Iperf [13]. Job-related states can be obtained either by a piggyback measurement of the execution time during workflow executions, or a regular "heartbeat" measurement if there is no chance for piggyback measurements. The benefit is that, we can obtain some history data as a by-product of workflow executions without additional cost.

Data maintenance. A naive sampling method for the MC implementation can be extremely inefficient to achieve a high accuracy. To make the distribution calculations more efficient, we maintain system state calibrations in the form of histograms and adopt a nonuniform sampling method to reduce the sampling size while preserving the desired optimization accuracy. The number of bins in a histogram is carefully selected to balance the tradeoff between optimization accuracy and overhead. Based on our sensitivity studies, we set this parameter to 200 by default. We discretize the distributions of system state values with nonuniform intervals, where more samples are taken at variable values with higher probability. Assume that the sample size for a r.v. X is N, then for $\forall x_i$ ($i \in 0 \ldots, N-2$), we have $P(x_{i+1}) - P(x_i) = \frac{1}{N}$.

Data update. Cloud dynamics histograms are used by *Prob* for probabilistic evaluations of solutions. We adopt a window-based method to predict the distributions of cloud dynamics in the future. We simply assume that the distribution of a dynamics factor in the current window is the same as that of the previous window. We update system state calibrations at the end of every window.

Table 1: Description of APIs in the runtime library.

API	Parameter	Return
$V(\vec{P}) \leftarrow$ *PreProcessing*(W, s, t)	W: The workflow to be optimized s, t: Source and target node ID	$V(\vec{P})$: A set of paths $\vec{P}$ starting from s to t in the workflow W
$P' \leftarrow$ *TaskBundling*(P) $P' \leftarrow$ *TaskClustering*(P)	P: The path to be optimized	P': The path after optimization
$P_c \leftarrow$ *Max*(P_a, P_b) $P_c \leftarrow$ *Add*(P_a, P_b) $p \leftarrow$ *Compare*(P_a, P_b)	P_a, P_b: Two probability distributions	P_c: The max/sum distribution of P_a, P_b p: Probability of $P_a > P_b$
$(P_1, P_2) \leftarrow$ *PartialEval*(s_1, s_2)	s_1, s_2: Two found solutions	P_1, P_2: Evaluated distributions of s_1 and s_2

To this method, one important parameter is the window size. Different kinds of cloud dynamics may have different suitable window sizes. For each dynamics factor, we calculate the Bhattacharyya distance [3] between the real and predicted distributions for different window sizes using historical data. We select the window size which generates the shortest Bhattacharyya distance for the window-based distribution prediction. According to our sensitivity studies, we set this parameter to one day by default for cloud I/O and network performance distributions.

5.2 Runtime Library

We develop a runtime library to expose the pruning techniques of *Prob*. Table 1 summarizes the three types of APIs in the library.

Pre-processing APIs. We provide the *PreProcessing()* API, which implements the path enumeration, critical path pruning and path binding optimizations. It takes a workflow, a source node and a target node as input and returns a set of paths from the source node to the target node as output. The output paths are candidates of the critical path. This API can be called before the solution search.

Workflow-related APIs. We provide four APIs for the workflow-specific optimizations. The *TaskBundling()* and *TaskClustering()* APIs implement task bundling and task clustering optimizations, respectively. Each API takes a path as input, and return the optimized path with bundled/clustered nodes as output. The *Max()* and *Add()* APIs take two probability distributions as input and return their maximum and sum distributions as output, respectively. These APIs are useful for implementing the solution evaluation logic with performance objectives, e.g., calculating the workflow execution time distribution.

Distribution-related APIs. The *PartialEval()* API takes two found solutions as input and returns their partial evaluation results as output. The outputs can be used to compare the relative optimality of the two solutions. The comparison can be performed with the *Compare()* API, which takes two probability distributions as input and return their comparison result as output. Users can utilize the APIs to implement the solution searching logic, e.g., comparing the evaluations of found solutions to find a good one.

We take the budget-constrained scheduling problem as an example to show how users can modify their existing method using provided APIs. Algorithm 1 shows the modifications users need to make when incorporating probabilistic optimizations (right) into the existing search algorithm [32] introduced in Section 3.2 (left). Users mainly need to modify their state evaluation logics using our APIs (partial solution evaluation is omitted for clarity of presentation). Given a workflow W to optimize, users first call the PreProcessing() API to get a pruned set of critical paths P (Line 2). Given a found solution, users assign the instance configurations to each task of the workflow and call the TaskBundling() and TaskClustering() APIs to simplify the paths (Line 7). Note that, for fair comparison, we implement the pre-processing, task bundling and task clustering optimizations for both methods. The Add() and Max() APIs are used to evaluate the distributions of paths and the distribution of workflow (Line 8-15). Lines 17-19 show how to use the Compare() API to maintain the best found solution. With the APIs in the runtime library, users need little changes (highlighted with underlines) to their existing implementation in order to enable probabilistic optimizations.

Algorithm 1 Static (left) and probabilistic (right) algorithms for budget-constrained scheduling on workflow W.

Static (left):

```
1:  Preserve the best solution CurBest;
2:  P = PreProcessing(W, entry, exit);
3:  ...                                          ▷ State traversal
4:  Given a solution s, assign instance configurations in s to each task in W;
5:  Initialize workflow execution time as time = 0;
6:  for each path in P do
7:      TaskBundling(TaskClustering(path));
8:      Initialize the length of path as t = 0;
9:      for each task tk on path do
10:
11:
12:         t = t + t_tk;
13:     if t ≥ time then
14:         time = t;
15:
16: ...                                          ▷ Evaluate the expected cost
17: if cost ≤ B then
18:     if time < CurBest.time then
19:
20:         CurBest = s;
21: ...                                          ▷ Go back to state traversal
```

Probabilistic (right):

```
Preserve the best solution CurBest;
P = PreProcessing(W, entry, exit);
...                                          ▷ State traversal
Given a solution s, assign instance configurations in s to each task in W;
Define workflow execution time distribution Time;
for each path in P do
    TaskBundling(TaskClustering(path));
    Define the length distribution of path as T;
    for each task tk on path do
        if tk is the first task in path then
            T = T_tk;
        else T = Add(T, T_tk);
    if path is the first path in P then
        Time = T;
    else Time = Max(Time, T)
...                                          ▷ Evaluate the expected cost
if cost ≤ B then
    if Compare(CurBest.Time, Time) > 0.5 then
        CurBest = s;
...                                          ▷ Go back to state traversal
```

6 EVALUATIONS

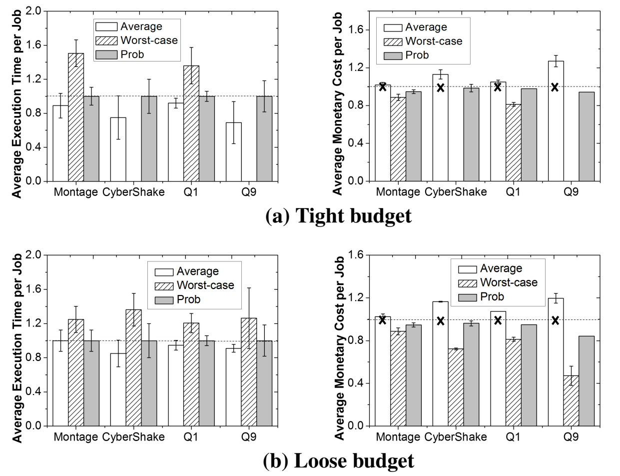
We evaluate the effectiveness and efficiency of *Prob* using the budget-constraint scheduling problem as an example. Experiments on more use cases can be found in our technical report [33]. To demonstrate the effectiveness of probabilistic optimizations, we compare existing state-of-the-art workflow optimization approaches with and without *Prob* incorporation. For efficiency, we compare the optimization overhead of *Prob* with the overhead of MC. We run the compared approaches on a machine with 24GB DRAM and a 6-core Intel Xeon CPU. Workflows are executed on Amazon EC2 or a cloud simulator.

6.1 Experimental Setup

Data processing workflows. We consider data processing workflows from scientific and data analytics applications, denoted as scientific and MR workflows, respectively. They are important applications in HPC and Big Data areas.

The tested scientific workflows include the I/O-intensive Montage workflow and data-intensive CyberShake workflow. We create Montage workflows with 10,567 tasks each using Montage source code. The input data are the 2MASS J-band images covering 8-degree by 8-degree areas [20]. Since CyberShake is not open-sourced, we construct synthetic workflows with 1000 tasks each using the widely used workflow generator [24].

The MR workflows include two TPC-H queries, Q1 and Q9, expressed as Hive programs. Q1 is a relatively simple selection query, and Q9 involves multiple joins. Both queries have order-by



(a) Tight budget

(b) Loose budget

Figure 6: Normalized results of budget-constrained scheduling problem. Cross marks stand for budget violations.

Table 2: Hours/costs of different instance types used during one CyberShake execution under loose budget.

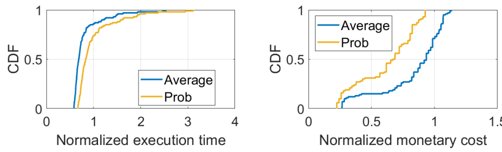
	m1.small	m1.medium	m1.large	m1.xlarge
Average	0	0	161h/$28.4	16h/$5.7
Worst-case	507h/$22.3	0	0	0
Prob	0	0	169h/$29.6	0

and group-by operators. The input data size is around 500GB (the scale factor is 500) and is stored on the local HDFS. A Hive query is usually composed of several MR jobs. Q1 is composed of two MR jobs and Q9 is composed of seven MR jobs.

Implementation. We conduct our experiments on both real clouds and simulator to study the workflow optimization problems in a controlled and in-depth manner. On Amazon EC2, we utilize an existing workflow management system [7] to execute scientific workflows, and deploy Hadoop and Hive to run the TPC-H queries. We adopt an existing cloud simulator [32] designed based on CloudSim [4] to simulate the dynamic cloud environment. As CyberShake is not open-sourced, we use trace-driven simulations for all CyberShake evaluations.

Parameter setting. In each experiment, we submit 100 jobs for each workflow with job arrival time in a Poisson distribution ($\lambda = 0.1$ by default), which is sufficiently large for measuring the stable performance. We use four types of Amazon EC2 instances with different prices and computational capabilities, including m1.small, m1.medium, m1.large and m1.xlarge. We compare *Prob* with two static algorithms named *Average* and *Worst-case*, which optimize the performance of workflows using the expected and the 99-th percentile of cloud dynamics distributions, respectively. The static algorithms adopt the search method [32] as shown in Algorithm 1.

We set a loose budget and a tight budget as $\frac{B_{min}+3B_{max}}{4}$ and $\frac{3B_{min}+B_{max}}{4}$, respectively, where B_{min} and B_{max} are the expected cost of executing all tasks in the workflow on m1.small instances and on m1.xlarge instances, respectively. Given a budget, we run the compared algorithms for 100 times and compare average monetary cost and execution time results.



(a) Execution time **(b) Monetary cost**

Figure 7: Cumulative distributions of normalized execution time and monetary cost of Cybershake under loose budget.

6.2 Optimization Effectiveness

Figure 6a and 6b show the average execution time and monetary cost optimization results of the compared algorithms when the budget is set to tight and loose, respectively. The execution time results are normalized to that of *Prob* and the monetary cost results are normalized to the budget. In the following, the error bars show the standard deviation of the results. We have the following observations.

Compared to Worst-case, *Prob* obtains better performance results while satisfying the budget constraint under all settings. *Prob* reduces the expected execution time of Montage, CyberShake, Q1 and Q9 by 51%, N/A, 36% and N/A under the tight budget, and by 24%, 37%, 19% and 26% under the loose budget. Worst-case cannot find a feasible solution for CyberShake and Q9 under the tight budget because these two workflows are more data- and network-intensive. As Worst-case tends to over-estimate the average execution time of workflows, it always chooses cheaper instance types than *Prob* to guarantee the budget, as shown in Table 2. The improvement of *Prob* over Worst-case is larger when the budget is tight. This is because cheap instances are chosen when the budget is tight and performance variations of workflows are more severe on cheap instances.

Compared to Average, *Prob* is able to guarantee the budget constraint under all settings. The Average method tends to under-estimate the expected execution time of workflows. As a result, the monetary cost estimated by Average for each found solution is lower than the real cost. Differences between the cost estimated by *Prob* and Average during solution search for Montage, CyberShake, Q1 and Q9 are up to 2%, 14%, 12% and 20%, respectively, under the tight budget. Under-estimation of the cost leads to infeasible solutions due to budget violations, as illustrated by the cross marks in Figure 6a and 6b. To further understand the impact of cloud dynamics to Average, we show the cumulative distributions of the monetary cost and execution time results of Cybershake under the loose budget. As shown in Figure 7b, among the 100 times of executions, only around 70% of results obtained by Average satisfy the budget constraint (i.e., normalized cost $\leq$ 1) while *Prob* can 100% guarantee the budget constraint.

Average performs especially poor on Q9 due to several reasons. First, due to the all-to-all structure of MR workflows, there are a large number of *MAX* operations when calculating the workflow execution time, which causes large errors with the static methods. Second, Q9 is composed of seven MR jobs, which is more complicated than Q1. The errors obtained on each level of Q9 accumulate and thus make Average seriously violating the budget constraint. Table 3 shows the differences between *Prob* and Average on the expected execution time from the entry to each level of the Q9 workflow structure.

The above observations demonstrate that, considering cloud performance dynamics gives more accurate estimations of workflow performance in the cloud, so that budget constraints can be satisfied and better optimization results can be obtained.

Table 3: Differences between *Prob* and Average on the expected execution time from entry task to each level of Q9.

level	0	1	2	3	4	5	6	7	8-13
diff. (%)	4.8	7.4	9.4	10.5	13.7	15.9	18.3	21.5	27.6

6.3 Comparison with MC

We compare *Prob* with MC method (Section 3.3) to evaluate the effectiveness and efficiency of our pruning techniques.

Effectiveness. We calculate the average ratio of optimized results between *Prob* and MC. The calculated ratio is 1.05, which means that *Prob* achieves a close optimization result as MC and thus demonstrates the effectiveness of *Prob*. This is mainly due to the fact that all pruning techniques in *Prob* can theoretically guarantee that the input probability distributions remain the same or similar after optimizations.

Efficiency. The average optimization overhead of *Prob* are 2.5s, 1.7s, 6.1s and 7.0s for Montage, CyberShake, Q1 and Q9 workflows, respectively. The average speedup over MC is 450x. We take a closer look at our pruning techniques to evaluate their individual effectiveness on reducing the overhead of *Prob*. With the pre-processing operations, the number of paths enumerated in a workflow can be greatly reduced. For example, the pre-processing operation reduces the number of paths from $219,452$ to one for the Montage workflow. The workflow-specific optimizations can reduce the path distribution evaluation overhead by 20% on average. The partial solution evaluation can reduce solution search overhead up to 78%.

The above observations demonstrate that, our pruning techniques can greatly reduce the optimization overhead while maintaining the effectiveness of probabilistic optimizations.

7 RELATED WORK

Workflow optimizations in the cloud. Performance and cost optimizations for data-centric workflows in the cloud have been widely studied [14, 15, 18]. Mao et al. [18] proposed an auto-scaling method to maximize workflow performance in the cloud under budget constraints. Malawski et al. [15] propose to optimize for workflow ensembles under both budget and deadline constraints. Kllapi et al. [14] proposed a generic optimizer for both constrained and skyline optimization problems of dataflows in the cloud. However, none of them has considered the impact of cloud dynamics.

Dynamic cloud environment. Many existing works have studied the performance dynamics in the cloud. Previous works have demonstrated significant variances on the cloud performance [9, 27]. The distribution model (histogram) is also adopted in the previous work [27] to measure and analyze the cloud performance variances. Recently, there are some studies proposing various methods such as dynamic scheduling and stochastic modeling to address the resource provisioning problem considering cloud dynamics (or uncertainties) [29]. However, those solutions are designed for a specific goal while *Prob* can be adopted by different resource provisioning methods to incorporate cloud dynamics.

Efficient probabilistic methods. The probabilistic distribution model has been adopted in different research domains to improve the optimization results in dynamic environments. In database field, efficiently evaluating probabilistic queries over imprecise data is a hot research topic. Many pruning mechanisms have been proposed to improve the efficiencies of answering probabilistic queries such as top-k [19], aggregations and nearest neighbor [21] on probabilistic databases [6]. Different from those studies, *Prob* is specially designed for the performance optimizations of data processing workflows. In big data processing, UP [16] is a probabilistic method which studies the uncertainty propogation in data processing systems to achieve bounded accurate data processing with uncertain data. However, this method assumes given probability distribution while *Prob* does not have any assumption on the distribution of cloud dynamics. 3Sigma [23] is another distribution-based method proposed for cluster scheduling considering runtime uncertainty. However, different from *Prob*, this work does not consider the uncertainty propagation problem in complicated job structures such as workflows, and experimented with mapper only jobs.

8 CONCLUSION

We propose a probabilistic optimization runtime named *Prob* for resource provisioning of workflows considering system variations. Specifically, we focus on the cloud system and model *cloud dynamics* as time-dependent random variables. *Prob* takes their *probability distributions* as optimization input to resource provisioning problems of workflows and thus can have a better view of system performance and generate more accurate optimization results. The main challenge of *Prob* is the large computation overhead due to complex workflow structures and the costly distribution calculations. To address this challenge, we propose three pruning techniques to simplify workflow structure and reduce the distribution evaluation overhead. We implement our techniques in a runtime library, which allows users to incorporate efficient probabilistic optimization into their existing resource provisioning methods. Experiments on real cloud show that probabilistic solutions can improve the performance by 51% compared to state-of-the-art static solutions while guaranteeing budget constraint, and our pruning techniques can greatly reduce the overhead of probabilistic optimization. As future work, we plan to study *Prob* on more use cases and different systems.

ACKNOWLEDGMENT

This work is in part supported by the National Natural Science Foundation of China (No. 61802260), the Guangdong Natural Science Foundation (No. 2018A030310440), the Shenzhen Science and Technology Foundation (No. JCYJ20180305125737520) and the Natural Science Foundation of SZU (No. 000370). Bingsheng He's research is partly supported by a MoE AcRF Tier 1 grant (T1 251RES1610) in Singapore. Reynold Cheng was supported by the Research Grants Council of HK (RGC Projects HKU 17229116, 106150091 and 17205115), the University of HK (104004572, 102009508 and 104004129) and the Innovation&Technology Commission of HK (ITF project MRP/029/18). Shadi Ibrahim's work is partly supported by the ANR KerStream project (ANR-16-CE25-0014-01) and the Stack/Apollo connect talent project.

REFERENCES

[1] Bilge Acun, Phil Miller, and Laxmikant V. Kale. 2016. Variation Among Processors Under Turbo Boost in HPC Systems. In *ICS '16*. 6:1–6:12.

[2] Omer Adam, Young Choon Lee, and Albert Y. Zomaya. 2017. Stochastic Resource Provisioning for Containerized Multi-Tier Web Services in Clouds. *TPDS* (2017).

[3] A. Bhattacharyya. 1943. On a measure of divergence between two statistical populations defined by their probability distributions. *Bulletin of the Calcutta Mathematical Society* 35 (1943), 99–109.

[4] Rodrigo N. Calheiros, Rajiv Ranjan, Anton Beloglazov, A. F. De Rose, and Rajkumar Buyya. 2011. CloudSim: A Toolkit for Modeling and Simulation of Cloud Computing Environments and Evaluation of Resource Provisioning Algorithms. *Softw. Pract. Exper.* 41, 1 (2011), 23–50.

[5] Reynold Cheng, Sarvjeet Singh, Sunil Prabhakar, Rahul Shah, Jeffrey Scott Vitter, and Yuni Xia. 2006. Efficient Join Processing over Uncertain Data. In *CIKM '06*.

[6] Nilesh Dalvi and Dan Suciu. 2007. Efficient Query Evaluation on Probabilistic Databases. *The VLDB Journal* 16, 4 (2007), 523–544.

[7] Ewa Deelman, Karan Vahi, Gideon Juve, Mats Rynge, Scott Callaghan, Philip J. Maechling, Rajiv Mayani, Weiwei Chen, Rafael Ferreira da Silva, Miron Livny, and Kent Wenger. 2015. Pegasus, a workflow management system for science automation. *FGCS* 46 (2015), 17–35.

[8] Sheng Di, Yves Robert, Frédéric Vivien, Derrick Kondo, Cho-Li Wang, and Franck Cappello. 2013. Optimization of Cloud Task Processing with Checkpoint-restart Mechanism. In *SC '13*. 64:1–64:12.

[9] Benjamin Farley, Ari Juels, Venkatanathan Varadarajan, Thomas Ristenpart, Kevin D. Bowers, and Michael M. Swift. 2012. More for Your Money: Exploiting Performance Heterogeneity in Public Clouds. In *SoCC '12*.

[10] M. Reza Hoseinyfarahabady, Hamid R.D. Samani, Luke M. Leslie, Young Choon Lee, and Albert Y. Zomaya. 2013. Handling Uncertainty: Pareto-Efficient BoT Scheduling on Hybrid Clouds. In *ICPP '13*. 419–428.

[11] Botong Huang and Jun Yang. 2017. Cumulon-D: data analytics in a dynamic spot market. *VLDB* (2017), 865–876.

[12] Qingjia Huang, Sen Su, Jian Li, Peng Xu, Kai Shuang, and Xiao Huang. 2012. Enhanced Energy-Efficient Scheduling for Parallel Applications in Cloud. In *CCGRID '12*. 781–786.

[13] Iperf. 2017. *https://github.com/esnet/iperf*. accessed on July 2017.

[14] Herald Kllapi, Eva Sitaridi, Manolis M. Tsangaris, and Yannis Ioannidis. 2011. Schedule Optimization for Data Processing Flows on the Cloud. In *SIGMOD '11*.

[15] Maciej Malawski, Gideon Juve, Ewa Deelman, and Jarek Nabrzyski. 2012. Cost- and Deadline-constrained Provisioning for Scientific Workflow Ensembles in IaaS Clouds. In *SC '12*. 22:1–22:11.

[16] Ioannis Manousakis, Íñigo Goiri, Ricardo Bianchini, Sandro Rigo, and Thu D. Nguyen. 2018. Uncertainty Propagation in Data Processing Systems. In *SoCC*.

[17] Ming Mao and Marty Humphrey. 2011. Auto-scaling to Minimize Cost and Meet Application Deadlines in Cloud Workflows. In *SC '11*. Article 49, 12 pages.

[18] Ming Mao and Marty Humphrey. 2013. Scaling and Scheduling to Maximize Application Performance Within Budget Constraint in Cloud Workflows. In *IPDPS'13*. 67–78.

[19] Luyi Mo, Reynold Cheng, Xiang Li, David W. Cheung, and Xuan S. Yang. 2013. Cleaning uncertain data for top-k queries. In *ICDE '13*. 134–145.

[20] NASA/IPAC. 2005. Montage Archive. http://hachi.ipac.caltech.edu:8080/montage/. (2005).

[21] Johannes Niedermayer, Andreas Züfle, Tobias Emrich, Matthias Renz, Nikos Mamoulis, Lei Chen, and Hans-Peter Kriegel. 2013. Probabilistic Nearest Neighbor Queries on Uncertain Moving Object Trajectories. *VLDB* (2013).

[22] Zhonghong Ou, Hao Zhuang, Jukka K. Nurminen, Antti Ylä-Jääski, and Pan Hui. 2012. Exploiting Hardware Heterogeneity Within the Same Instance Type of Amazon EC2. In *HotCloud'12*.

[23] Jun Woo Park, Alexey Tumanov, Angela Jiang, Michael A. Kozuch, and Gregory R. Ganger. 2018. 3Sigma: Distribution-based Cluster Scheduling for Runtime Uncertainty. In *EuroSys '18*. 1–17.

[24] Pegasus. 2014. Workflow Generator. https://confluence.pegasus.isi.edu/display/pegasus/WorkflowGenerator. (2014).

[25] Deepak Poola, Kotagiri Ramamohanarao, and Rajkumar Buyya. 2014. Fault-tolerant Workflow Scheduling using Spot Instances on Clouds. In *ICCS '14*.

[26] Martin Rinard. 2006. Probabilistic Accuracy Bounds for Fault-tolerant Computations That Discard Tasks. In *ICS '06*. 324–334.

[27] Jörg Schad, Jens Dittrich, and Jorge-Arnulfo Quiané-Ruiz. 2010. Runtime Measurements in the Cloud: Observing, Analyzing, and Reducing Variance. *VLDB* (2010), 460–471.

[28] Gurmeet Singh, Mei-Hui Su, Karan Vahi, Ewa Deelman, Bruce Berriman, John Good, Daniel S. Katz, and Gaurang Mehta. 2008. Workflow Task Clustering for Best Effort Systems with Pegasus. In *MG '08*. 9:1–9:8.

[29] Andrei Tchernykh, Uwe Schwiegelsohn, Vassil Alexandrov, and El ghazali Talbi. 2015. Towards understanding uncertainty in Cloud computing resource provisioning. In *ICCS '15*. 1772–1781.

[30] Ashish Thusoo, Zheng Shao, Suresh Anthony, Dhruba Borthakur, Namit Jain, Joydeep Sen Sarma, Raghotham Murthy, and Hao Liu. 2010. Data Warehousing and Analytics Infrastructure at Facebook. In *SIGMOD '10*. 1013–1020.

[31] Jia Yu, Rajkumar Buyya, and Chen Khong Tham. 2005. Cost-Based Scheduling of Scientific Workflow Applications on Utility Grids. In *e-Science '05*. 140–147.

[32] Amelie Chi Zhou, Bingsheng He, Xuntao Cheng, and Chiew Tong Lau. 2015. A Declarative Optimization Engine for Resource Provisioning of Scientific Workflows in IaaS Clouds. In *HPDC '15*. 223–234.

[33] Amelie Chi Zhou, Bingsheng He, Shadi Ibrahim, and Reynold Cheng. 2019. *Incorporating Probabilistic Optimizations for Resource Provisioning of Cloud Workflow Processing*. Technical Report 2019-TR-Prob. https://bit.ly/2ZrEGHy.